Scale dependence of landscape metrics and their indicatory value for nutrient and organic matter losses from catchments

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Abstract

We investigated scale dependence of landscape metrics and the relationship between land use parameters and FRAGSTATS-based landscape metrics (edge density (ED), patch density (PD), mean shape index (SHAPE_MN), mean euclidean nearest neighbor index (ENN_MN), contagion (CONTAG), patch richness density (PRD), and Shannon’s diversity index (SHDI)) and nutrient/organic-matter-based water quality indicators (BOD₇ and COD₅K₅O₄ values, total-N and total-P concentrations in water) in 24 catchments with various land use patterns in Estonia. We used the Basic Map of Estonia (1:10,000), the Base Map of Estonia (1:50,000) and the CORINE Land Cover Map (1:100,000). In scale analysis, we calculated landscape metrics on artificial and real landscapes. Scale analysis showed that responses of landscape metrics to changing grain size vary among landscapes and metrics. Analysis of artificial landscapes showed that mean euclidean nearest neighbor distance and contagion are directly dependent on grain size and should therefore be used carefully. When finding relationships between landscape metrics and water quality indicators, significant differences between the relationships derived from the Base Map and the CORINE Land Cover Map were found. In the case of the Base Map, landscape metrics correlated strongly with land use and showed no expected relationships with water quality data. This underlines the importance of land use classification in such kind of analysis. Correlation between the landscape metrics calculated on the basis of the CORINE Land Cover Map and water quality data was stronger than in the case of the Base Map. The COD₅K₅O₄ value significantly correlated with all land use types. Except for the BOD₇ value, all the water quality indicators showed significant correlation with urban land use proportions. Strong relationship between the patch density and the COD₅K₅O₄ value is most likely caused by the fact that both parameters were significantly correlated with the proportion of natural areas. As the landscape metrics depend on pixel size, topographic scale, and land use classification, and as the effect of land use on water quality in catchments is the most significant of the factors, it was impossible to separate the influence of land use pattern from the influence of FRAGSTATS-based landscape metrics.

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1. Introduction

Scaling issues were first recognized by cartographers who – making a reduced model of geographic space – had to generalize. For a cartographer, working out a good – clear and informative – map, the subjective side, the semiotic problems of cartographic communication, are rather central to making a goal-oriented presentation. According to cartographic traditions, the larger the map scale the more detailed is the presentation. Upscaling (movement towards a smaller map scale) means (besides many technical details of the geometric generalization) a movement upwards in the hierarchy of objects, and is related to the semantic generalization (Jones, 1997). The hierarchy theory discerns levels of organization and levels of observation (Ahl and Allen, 1996) and regards scale not as an intrinsic attribute of a system property, but as a constraint imposed by the observer (Allen and Hoekstra, 1991).

The fact that the results of spatial data analysis depend on data aggregation methods and the zoning scheme was recognized by quantitative geographers long ago. Its general formulation is known as the modifiable areal unit problem (MAUP) made by Openshaw and Taylor (1981). There exists broad choice of literature on this topic in landscape ecology, from classic authors (Turner and Gardner, 1990) and textbooks (Farina, 1998, 2000; Turner et al., 2001) to new papers (Jelinski and Wu, 1996; Wu and Qi, 2000; Hay et al., 2001; Wu et al., 2002).

MAUP in landscape ecological context consists of three related aspects: how the grain size, zoning and areal extent of investigation influence the results and how to find their optimal values for each concrete case. In addition, landscape pattern reveals fractal behavior, which should be studied with a multi-scale approach (Milne, 1991a; Nikora et al., 1999).

This scale-dependence of spatial pattern has been described by Turner et al. (1989); Milne (1991b); Costanza and Maxwell (1994); Wickham and Ritters (1995); Moody and Woodcock (1995); Cain et al. (1997); Wu et al. (2000); Gergel and Turner (2002); Lausch and Herzog (2002).

Although these three aspects are closely interrelated, their relative importance depends on the conceptual basis of investigation. If the phenomena under consideration are regarded as fields, e.g., De Cola (1994), the raster model is essential and grain size has primary importance. Remote sensing images are commonly used. Zoning and areal extent are a priori not related to landscape ecology but need to be identified during the analysis phase. If the raster model is used for analysis, then some geometric generalization takes place.

The influence of land use on water quality in streams is scale dependent and varies in time and space (Young et al., 1987; Behrendt et al., 2002; Buck et al., 2004). Numerous studies have found the landscape structure to be the main factor influencing the nutrient and organic matter runoff from watersheds. This has been shown at the global scale (Turner et al., 2003), as well as at the regional and local scales for catchments of dominantly agricultural use (Young et al., 1987; Arheimer and Brandt, 2000; McDowell et al., 2001; Steegen et al., 2001; Cao et al., 2003; Davenport et al., 2003; Haggard et al., 2003; Suttles et al., 2003; Buck et al., 2004; Nair and Graetz, 2004), and for forested areas (Wickham et al., 2003), and for heterogeneous multifunctional landscapes (Stål Nacke et al., 1999; Mander et al., 2000; Baker et al., 2001; Chen et al., 2002; Steinhardt and Volk, 2003). In relation to material export, different landscape metrics have been used for the description of landscape structure in catchments: areas of landscape elements and distances of landscape elements from water bodies (Thierfelder, 1998): topography elements (Jones et al., 2001; Cao et al., 2003), presence of riparian zones (Kuusmets and Mander, 2001; Baker et al., 2001; Jones et al., 2001; Gergel et al., 2002; McClain et al., 2003) and wetlands (Trelle and Palermi, 2002), and various diversity metrics (Jones et al., 2001; Chen et al., 2002; Gergel et al., 2002). Several studies have shown a good detectability of stream water quality using remote sensing data (Griffith et al., 2002; Davenport et al., 2003). Johnson et al. (2001) have found that landscape measurements alone, obtained solely from remotely sensed data, can explain about 75% of the water quality variability in catchments.

Hundreds of landscape metrics have been proposed by various researchers to analyse the landscape structure. Most of them are covered by the computer program FRAGSTATS (McGarigal and Marks, 1995).
Since the emergence of FRAGTATS (the first version appeared in 1993 but broad use started with the public domain v.2.0—McGarigal and Marks, 1995) the measures and methods incorporated in this software are very widely used. Despite the several weaknesses of FRAGSTATS it has become a de facto standard tool for calculating landscape metrics. Therefore, we limited ourselves to the possibilities offered by FRAGSTATS.

To control how landscape metrics respond to changing grain size, extent, number of zones, the direction of analysis, etc., landscape simulators are applied (e.g., Li and Reynolds, 1994). Gardner et al. (1987) introduced the concept of neutral models into landscape ecology. The aim of a neutral model is to have “an expected pattern in the absence of specific landscape processes” (ibid). In order to have a random pattern, the first applications of this concept stemmed from the percolation theory (Gardner and O’Neill, 1991), but different types of regular artificial landscapes are also used (De Cola, 1994; Li and Reynolds, 1994).

The aim of our study was to investigate relationships between the land use parameters and FRAGSTATS-based landscape metrics and nutrient/organic-matter-based water quality indicators in catchments with various land use patterns using different spatial data resolutions.

Our investigation consisted of two main parts:

1. Examination of selected landscape metrics at different grain sizes for real and artificial landscapes. Recently, Wu et al. (2002) who used different empirical landscape data, grouped the effects of changing grain size into three general types:
   - Type I: predictable responses with simple scaling relations;
   - Type II: staircase-like responses with no simple scaling relations;
   - Type III: erratic responses exhibiting no general scaling relations.

   We used the same typification.

2. Application of the acquired knowledge to test structural indexes as indicators of nutrients’ wash-off using measured runoff-data and existing maps.

2. Materials and methods

2.1. Scale dependence of landscape metrics

To examine the influence of spatial resolution (and other possible noise factors) on landscape metrics, we tested different artificial and real landscapes. The grain size (pixel size) was systematically changed from 10 m to 1000 m. The landscape metrics were analyzed using the computer program FRAGSTATS (McGarigal et al., 2002). As noted by many authors (O’Neill et al., 1999; Griffith et al., 2000; Wu et al., 2002), many of the landscape metrics are correlated with each other. Therefore, we performed correlation analysis and picked those landscape metrics that did not correlate significantly with others. There was only one exception—patch density, which correlated with edge density, but is very often used. We used the following landscape metrics: edge density (ED), patch density (PD), mean shape index (SHAPE_MN), mean euclidean nearest neighbor index (ENN_MN), contagion (CONTAG), patch richness density (PRD), and Shannon’s diversity index (SHDI) (Table 1).

2.1.1. Artificial landscapes

Computer programs (we used Idrisi Kilimanjaro) allow us to generate raster patterns with textures of our choice. We tested dependence on grain size for different types of regular landscapes (Fig. 1): “chessboards” (two-colour, six-colour), checked structures (regular and random mixture of different squares), and linear and radial structures.

2.1.2. Real landscapes

The land use data for real landscapes was derived from the Estonian Basic Map (1:10,000), as it was the most accurate map available (Table 2). As the Basic Map was not available for all the catchments studied (only the Poriõõ River catchment was covered), we used two additional areas with considerably different study sites – “South Estonia” and “Northeast Estonia” (Fig. 2) – for the landscape structure analysis. The South-Estonian landscape is fragmented and dominated by agricultural and urban land uses, while the Northeast Estonian landscape is more homogenous and less influenced by human activities (Fig. 3). The extent of the study sites for landscape structure analysis (Northeast Estonia and South...
Estonia, Fig. 2) was set at 15 km × 15 km = 225 km² using core areas. The Porijõgi catchment has natural boundaries and a size of 241 km²; a major part of it is located on the Otepää Heights, and the landscape is very fragmented and dominated by semi-natural grasslands and forests (Fig. 3; Mander et al., 2000).

The original data was in vector format and for landscape analysis it was converted into raster format. Changing grain size, we calculated the necessary metrics (Table 1).

2.2. Indicators

To find relationships between landscape metrics and nutrient and organic matter runoff in catchments, we used land use and land cover maps of 24 catchments (Fig. 2). Data used for the calculation of landscape metrics was derived from the Estonian Base Map (1:50,000) and the CORINE Land Cover Map (1:100,000). Due to computational limitations, the spatial resolution for both maps was 30 m. The land use and land cover types identified on these two maps are listed in Table 2. The CORINE Land Cover Map has more land cover types than the Estonian Base Map, although the level of generalization is greater (Fig. 4).

We used the water quality data (BOD₇ and COD₉MnO₄ values, total-N and total-P concentrations in water samples from closing weirs of studied rivers, mg l⁻¹) from the Estonian Environmental Monitoring Programme database. The disadvantage of this data was its dependence on point pollution sources (towns, factories). However, the relation between the biological oxygen demand (BOD₇) and the chemical oxygen demand (determined on the basis of potassium permanganate; COD₉MnO₄) helps to distinguish between the anthropogenic (mostly point pollution) sources and natural/semi-natural sources of pollution. In particular, high BOD₇ values indicate the presence of point-pollution sources (urban and industrial areas, settlements), whereas the COD₉MnO₄ value is high in

| Table 1 |
| List of landscape metrics used in the study (based on McGarigal et al., 2002) |
| Landscape metrics | Description |
| Edge density (ED) | The total length of all edge segments per ha for the landscape of consideration (unit: m/ha) |
| Patch density (PD) | The number of patches per unit area |
| Mean shape index (SHAPE_MN) | A patch-level shape index averaged over all patches in landscape: SHAPE_MN = \( \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left( \frac{p_{ij}}{a_{ij}} \right)}{N} \), where \( p_{ij} \) is the perimeter and \( a_{ij} \) is the area of patch \( ij \), and \( N \) is the total number of patches in the landscape (unitless) |
| Mean euclidean nearest neighbour index (ENN_MN) | A patch level the distance (m) to the nearest neighbouring patch of the same type, based on shortest edge-to-edge distance is averaged over all patches in landscape. ENN_MN = \( \frac{1}{N} \sum_{i=1}^{n} \sum_{j=1}^{n} h_{ij} \), where \( h_{ij} \) distance from patch \( ij \) to nearest neighbouring patch of the same type (class), based on patch edge-to-edge distance, computed from cell centre to cell centre, and \( N \) is the total number of patches in the landscape (unit: m) |
| Contagion (CONTAG) | Indicates the aggregation of patches. CONTAG = \( \left[ 1 + \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left( \frac{g_{ik}}{\ln(P_{i})} \right) \left( \ln \left( \frac{g_{ik}}{\sum_{k=1}^{m} \sum_{l=1}^{m} g_{kl}} \right) \right) \right] \times 100\% \), where \( P_{i} \) is the proportion of the landscape occupied by patch type \( i \); \( g_{ik} \) is the number of adjacencies between pixels of patch types (classes) \( i \) and \( k \) based on the double-count method; and \( m \) is the number of patch types (classes) in the landscape (incl. landscape border if present (unit: %)) |
| Patch richness density (PRD) | The number of patch types per unit area (unit: patches per 100 ha) |
| Shannon’s diversity index (SHDI) | Based on information theory, indicates the patch diversity in landscape: SHDI = \( -\sum_{i=1}^{m} \left( P_{i} \ln P_{i} \right) \), where \( P_{i} \) is the proportion of the landscape occupied by patch type \( i \) (unitless) |
natural areas with a high percentage of swamps, fens and bogs (Behrendt et al., 2002). Therefore, the COD_{K_MnO_4} correlates well with the widely used dissolved organic carbon (DOC) value (Qualls and Richardson, 2003).

Runoff of nutrients and organic matter is usually shown in kg ha\(^{-1}\) yr\(^{-1}\). As we did not have the required runoff-data, we used averaged annual concentrations (mg l\(^{-1}\)) of nutrients and organic matter in river waters.

The same landscape metrics were analyzed as in artificial and real landscapes analysis (Table 1). For statistical analysis of data, the computer program STATISTICA 6.0 was used. According to the Kolmogorov–Smirnov test for normality, none of the variables under consideration were normally distributed; therefore, the Spearman Rank Order Correlation was performed in order to characterize the relation between different parameters. Level of significance \(\alpha = 0.05\) was accepted in all cases.

Fig. 1. Artificial landscapes used in scale analysis.
Table 2
Land use and land cover types in real landscapes and study catchments

<table>
<thead>
<tr>
<th>Basic Map 1:10,000</th>
<th>Base Map 1:50,000</th>
<th>CORINE Land Cover Map 1:100,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lakes</td>
<td>Lakes</td>
<td>Lakes</td>
</tr>
<tr>
<td>Water courses</td>
<td>Water courses</td>
<td>Water courses</td>
</tr>
<tr>
<td>Forests</td>
<td>Agricultural land</td>
<td>Non-irrigated arable land</td>
</tr>
<tr>
<td>Small ponds</td>
<td>Urban</td>
<td>Urban</td>
</tr>
<tr>
<td>Young forests</td>
<td>Mine</td>
<td>Mine</td>
</tr>
<tr>
<td>Cultivated grasslands</td>
<td>Dump site</td>
<td>Dump site</td>
</tr>
<tr>
<td>Orchards</td>
<td>Fen</td>
<td>Inland marshes</td>
</tr>
<tr>
<td>Fallow lands</td>
<td>Peat field</td>
<td>Peat bogs</td>
</tr>
<tr>
<td>Buildings</td>
<td>Wetland</td>
<td>Deciduous forests</td>
</tr>
<tr>
<td>Graveyards</td>
<td>Airport</td>
<td>Green urban areas</td>
</tr>
<tr>
<td>Sparsely vegetated areas</td>
<td>Sport and Leisure facilities</td>
<td></td>
</tr>
<tr>
<td>Fens</td>
<td></td>
<td>Fruit trees and berry plantations</td>
</tr>
<tr>
<td>Arable lands</td>
<td>Pastures</td>
<td>Coniferous forest</td>
</tr>
<tr>
<td>Streets</td>
<td></td>
<td>Mixed forest</td>
</tr>
<tr>
<td>Yards</td>
<td>Natural grasslands</td>
<td>Natural grassland</td>
</tr>
<tr>
<td>Natural grasslands</td>
<td></td>
<td>Moors and heath land</td>
</tr>
<tr>
<td>Raised bogs</td>
<td></td>
<td>Sparsely vegetated areas</td>
</tr>
<tr>
<td>Recreational open space</td>
<td></td>
<td>Bushes</td>
</tr>
<tr>
<td>Bushes</td>
<td></td>
<td>Salt marshes</td>
</tr>
<tr>
<td>Burnt woodland</td>
<td>Peat fields</td>
<td>Peat fields</td>
</tr>
<tr>
<td>Peat fields</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 2. Location of study catchments and study sites for landscape structure analysis (Northeast Estonia and South Estonia, shown as quadrates).
3. Results and discussion

3.1. Scale dependence of landscape metrics

3.1.1. Artificial landscapes

Analysis of 10 × 10 and 50 × 50 chessboard showed that the value of PD does not change much, before the grain size exceeds patch size. However, in the case of the 45° rotated chessboard, the fluctuation in the response curve indicated that the orientation of patches is also important when changing grain size (Fig. 5). In the case of 2-level landscapes, response curves of PD were quite similar (Fig. 5). Values of PD decreased sharply at 100 m grain size and then fluctuated slightly as the small patches disappeared and appeared in the landscape. This indicates the influence of small patches on values of PD.

ED responses to changing grain size were similar to PD. This is because ED correlates with PD—it is mostly influenced by the same factors (size and number of patches) as PD.

In the case of the 10 × 10 and 50 × 50 chessboard the values of SHAPE_MN were 1, because the landscape consisted of squares. Values calculated on six-type and two-level landscapes decreased until they reached a value of 1.0 (Fig. 5). Values of SHAPE_MN start to approach 1.0 because more and more patches contain only one pixel and the decrease in the response curve is more rapid since the landscape consists of small patches.

Values of ENN_MN increase linearly in the case of 10 × 10, 50 × 50 and 45° rotated 10 × 10 chessboards (Fig. 5), although in the case of the structure of 10 × 10 chessboard does not change and distances...
Fig. 5. Effects of changing grain size on landscape metrics calculated on artificial landscapes.
between neighbors are the same. Mean nearest neighbor distance measures distance \( m \) to the nearest neighboring patch of the same type, based on shortest edge-to-edge distance, computed from cell center to cell center (McGarigal et al., 2002). Therefore, it is directly dependent on pixel size. When grain size is growing then \( \text{ENN}_\text{MN} \) is increasing. Although if there are some rare small patches in the landscape that disappear, then values of \( \text{ENN}_\text{MN} \) may decrease with increasing grain size. In case of 16-type linear landscape, the value of \( \text{ENN}_\text{MN} \) is zero because there are no patches of the same type in landscape. For the same reason, the values of \( \text{ENN}_\text{MN} \) are zero in the case of the \( 50 \times 50 \) chessboard at 400 and 800 m grain size. Therefore, behavior of \( \text{ENN}_\text{MN} \) depends on landscapes configuration.

Contagion is strongly influenced by grain size (Fig. 5). In case of \( 10 \times 10 \) chessboard contagion decreases until 500 m grain size and then increases again, although the configuration of the landscape remains the same at 100, 500 and 1000 m grain size. Values calculated on \( 50 \times 50 \) chessboard increase when each patch contains only one pixel and decrease as patches consist of more than one pixel, which is opposite to the expected. Contagion should be zero at 1000 m, because each patch contains only one pixel and their interspersion is maximal.

Contagion is based on pixel adjacency proportions. Therefore, it is very dependent on grain size (Li and Reynolds, 1993; Riitters et al., 1996; Ricotta et al., 2003). Analysis of artificial landscapes showed that contagion is directly dependent on pixel size. In most cases, contagion decreases with increasing grain size, but there are exceptions. Contagion may actually increase with changing grain size if the landscape is very fragmented and small patches consisting one or two pixels start to disappear and larger patches of one type unite. Therefore, the behavior of contagion depends on landscape pattern.

PRD calculated on \( 10 \times 10, 50 \times 50 \) and 45° rotated \( 10 \times 10 \) landscapes did not change with increasing grain size, because the composition of the landscape was changeless, with only one exception: in the case of the \( 50 \times 50 \) chessboard, the value of PRD decreased to 0.01 since the landscape consisted of one patch at 400 m grain size. From Fig. 5, it can be seen that PRD is strongly influenced by number of patch types present in landscape. In the case of two-level landscapes, PRD values fluctuate as small patches disappear or appear in the landscape. Behaviour of SHDI was similar to PRD.

Values of diversity metrics, especially PRD, are mostly determined by the number of patch types present in a landscape (McGarigal et al., 2002). Therefore, their response to changing grain size depends on how the number of patch types varies in the landscape.

### 3.1.2. Real landscapes

Results are presented according to the landscape metrics grouping presented by Wu et al. (2002). Two landscape metrics belonged to Type I: ED and PD. These metrics had predictable responses to changing grain size (Fig. 6). However, the responses varied across landscapes. Values of metrics calculated on Porijõgi and the South Estonian landscape decreased rapidly and then reached a relatively constant value, whereas in the case of the Northeast Estonian landscape, the values of metrics decreased slightly. All response curves best fitted the logarithmic function \( R^2 > 0.95 \). The difference in patch density values between landscapes almost disappears at 400 m grain size.

Results of PD and ED calculated on maps with a different map scale showed a significant difference in values (Fig. 7). Metrics calculated on the Basic Map decreased rapidly until, at 500 m grain size, they reached the same level as values of calculated from the Base Map and the CORINE Land Cover Map. The reason for this is different generalization and classification. Values of metrics calculated on large-scale maps tend to decrease more rapidly with changing grain size than values of metrics calculated on small-scale maps. Apparently topographic scale (generalization, classification) seems to have significant effect on values of landscape metrics. In other words, topographic scale holds the key to both the zoning question and the scale question (MAUP). At some spatial resolutions there is no point in comparing metrics calculated on maps with different topographic scale.

Both diversity metrics (PRD and SHDI) were classified as Type II. PRD and SHDI decreased stepwise with increasing pixel size (Fig. 6). The decrease in SHDI was not as obvious as that in values of PRD, and there were also some increases in the response curve. The number of patch types existing in
the landscape determines the values of PRD and SHDI. Their response to increasing grain size is determined by how many patch types are eliminated by aggregation (Wu et al., 2002). Therefore, their value also depends on the aggregation method used. We used the central-point method. By the central-point method patch types are not eliminated permanently, i.e., a patch type that is eliminated at 200 m spatial resolution can reappear at 400 m pixel size. Therefore, PRD and SHDI also showed some increases in their values. These fluxes in the response curve can be explained by the fact that SHDI is sensitive to rare patch types. SHDI is influenced by number of patch types as well as their distribution in the landscape.

In case of different map scales, diversity metrics also decreased stepwise (Fig. 7). Metrics calculated on different maps did not reach the same value as Type I metrics did. Therefore, the dissimilarity between maps remains. Accordingly, diversity metrics are not so much influenced by generalization as by land use classification.
SHAPE_MN, ENN_MN, and CONTAG were classified as Type III metrics. These metrics did not have predictable responses to changing grain size (Fig. 6). SHAPE_MN decreased significantly up to a grain size of 100 m and from 200 m showed erratic responses to increasing grain size. CONTAG decreased in the case of all landscapes up to a grain size of 400 m, and then fluctuated with further increase in grain size for all landscapes. ENN_MN increased linearly at first, and then showed no predictable responses to increasing grain size.

These metrics did not show a very clear relationship with changing grain size at different map scales (Fig. 7). Values of SHAPE_MN and CONTAG decreased at first with increasing grain size but then showed erratic behavior. Surprisingly, values of SHAPE_MN are not the highest in the case of the large-scale map. The CORINE Land Cover Map had
the highest values of SHAPE_MN, because buildings that are rectangular were not represented there.

### 3.2. Indicators

#### 3.2.1. Results of the Base Map analysis

All water quality indicators except the BOD$_7$ value showed significant positive correlations with urban land-use proportions (Table 3). Only the COD$_{\text{KmnO}_4}$ values decreased when the proportion of urban land use in catchments increased. At the same time, the COD$_{\text{KmnO}_4}$ was significantly correlated with the proportion of natural areas, agricultural land use, and fens. While the total-P and total-N concentrations were negatively correlated with the proportion of natural areas, the COD$_{\text{KmnO}_4}$ value increased with an increasing proportion of natural areas.

Results of the Base Map analysis showed unexpectedly strong relationships between the land-use characteristics and landscape metrics (Table 4). This is probably caused by the specifics of the Base Map’s land-use classification. The landscape metrics PD, ED, ENN_MN, CONTAG, and SHDI significantly correlate with proportions of natural areas, agricultural land use, and urban land use. The SHAPE_MN and PRD showed no relationship with land use.

Landscape metrics showed unexpected relationships with runoff-data (Table 5). PD and ED correlated negatively with COD$_{\text{KmnO}_4}$ and correlation between PD and total-P was positive. SHDI relationship with total-P indicated unexpectedly greater total-P runoff from high-diversity landscapes and landscapes with low contagion.

### Table 3

<table>
<thead>
<tr>
<th>Proportion of natural areas</th>
<th>Proportion of agricultural land use</th>
<th>Proportion of fens, bogs, and mires</th>
<th>Proportion of urban land use</th>
</tr>
</thead>
<tbody>
<tr>
<td>BOD$_7$</td>
<td>$-0.13$</td>
<td>$0.05$</td>
<td>$-0.18$</td>
</tr>
<tr>
<td>COD$_{\text{KmnO}_4}$</td>
<td>$0.59$</td>
<td>$-0.69$</td>
<td>$0.55$</td>
</tr>
<tr>
<td>Total-N</td>
<td>$-0.44$</td>
<td>$0.40$</td>
<td>$-0.25$</td>
</tr>
<tr>
<td>Total-P</td>
<td>$-0.59$</td>
<td>$0.46$</td>
<td>$-0.09$</td>
</tr>
</tbody>
</table>

Significant correlation coefficients are in bold; \(p < 0.05\).

### Table 4

<table>
<thead>
<tr>
<th>Proportion of natural areas</th>
<th>Proportion of agricultural land use</th>
<th>Proportion of fens and bogs</th>
<th>Proportion of urban land use</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>$-0.70$</td>
<td>$0.77$</td>
<td>$-0.54$</td>
</tr>
<tr>
<td>ED</td>
<td>$-0.65$</td>
<td>$0.69$</td>
<td>$-0.39$</td>
</tr>
<tr>
<td>SHAPE_MN</td>
<td>$-0.29$</td>
<td>$0.18$</td>
<td>$0.14$</td>
</tr>
<tr>
<td>ENN_MN</td>
<td>$0.62$</td>
<td>$-0.59$</td>
<td>$0.31$</td>
</tr>
<tr>
<td>CONTAG</td>
<td>$0.78$</td>
<td>$-0.60$</td>
<td>$-0.04$</td>
</tr>
<tr>
<td>PRD</td>
<td>$0.29$</td>
<td>$-0.22$</td>
<td>$-0.29$</td>
</tr>
<tr>
<td>SHDI</td>
<td>$-0.69$</td>
<td>$0.46$</td>
<td>$0.19$</td>
</tr>
</tbody>
</table>

Significant correlation coefficients are in bold; \(p < 0.05\). See Table 2 for explanation of landscape metrics’ abbreviations.
3.2.2. Relationships based on CORINE Land Cover Map analysis

The correlation of land use structure with water quality data was similar to that found in the Base Map analysis (Table 6). The COD\textsubscript{K\textsubscript{MnO}_4} value significantly correlated with all land use types. For instance, the COD\textsubscript{K\textsubscript{MnO}_4} values are higher when fens and natural areas account for a high proportion of the catchment’s land use. Except the BOD\textsubscript{7} value, all the water quality indicators showed significant correlation with urban land use proportions.

The relationship between the land-use proportions and landscape metrics was the opposite of that found from the Base Map analysis (Table 7). For example, ED correlated positively with the proportion of urban land use, whereas SHAPE\_MN did not have any significant relationships with land use. The positive correlation between contagion and proportion of agricultural land use most probably is indicative of a greater patch aggregation in agricultural catchments.

The correlation between the landscape metrics calculated on the basis of the CORINE Land Cover Map, and water quality data (Table 8) was stronger than in the case of the Base Map (Table 5). The patch density significantly correlated with BOD\textsubscript{7} and COD\textsubscript{K\textsubscript{MnO}_4} values, which means that lower amounts of organic matter are washed out from the catchments with high PD values.

Presentation of selected land use data and landscape metrics in the same graph with certain water quality parameters allows us to visualize the multiple relationships (Figs. 8–14). For example, the patch density had a significant relationship with proportion of natural areas, whereas the BOD\textsubscript{7} value did not correlate with any land use parameters. Fig. 8 shows that, with increasing PD, the BOD\textsubscript{7} value decreases.

### Table 6
Spearman Rank Order Correlation between land use proportions based on the CORINE Land Cover Map and runoff-data

<table>
<thead>
<tr>
<th>Proportion of natural areas</th>
<th>Proportion of agricultural land use</th>
<th>Proportion of fens, bogs and mires</th>
<th>Proportion of urban land use</th>
</tr>
</thead>
<tbody>
<tr>
<td>BOD\textsubscript{7}</td>
<td>0.22</td>
<td>-0.22</td>
<td>-0.03</td>
</tr>
<tr>
<td>COD\textsubscript{K\textsubscript{MnO}_4}</td>
<td><strong>0.70</strong></td>
<td><strong>-0.81</strong></td>
<td><strong>0.55</strong></td>
</tr>
<tr>
<td>Total-N</td>
<td>-0.34</td>
<td>0.35</td>
<td>-0.27</td>
</tr>
<tr>
<td>Total-P</td>
<td><strong>-0.59</strong></td>
<td><strong>0.49</strong></td>
<td>-0.10</td>
</tr>
</tbody>
</table>

Significant correlation coefficients are in bold; \( p < 0.05 \).

### Table 7
Spearman rank correlation matrix between land-use proportions based on the CORINE Land Cover Map and landscape metrics

<table>
<thead>
<tr>
<th>Proportion of natural areas</th>
<th>Proportion of agricultural land use</th>
<th>Proportion of fens, bogs and mires</th>
<th>Proportion of urban land use</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td><strong>-0.42</strong></td>
<td>0.40</td>
<td>-0.12</td>
</tr>
<tr>
<td>ED</td>
<td>-0.05</td>
<td>0.04</td>
<td>0.08</td>
</tr>
<tr>
<td>SHAPE_MN</td>
<td><strong>0.57</strong></td>
<td><strong>-0.58</strong></td>
<td>0.34</td>
</tr>
<tr>
<td>ENN_MN</td>
<td>-0.33</td>
<td>0.28</td>
<td>-0.01</td>
</tr>
<tr>
<td>CONTAG</td>
<td>-0.38</td>
<td><strong>0.57</strong></td>
<td><strong>-0.57</strong></td>
</tr>
<tr>
<td>PRD</td>
<td>0.18</td>
<td>-0.16</td>
<td>-0.20</td>
</tr>
<tr>
<td>SHDI</td>
<td>-0.09</td>
<td>-0.13</td>
<td><strong>0.53</strong></td>
</tr>
</tbody>
</table>

Significant correlation coefficients are in bold; \( p < 0.05 \). See Table 2 for explanation of landscape metrics’ abbreviations.

### Table 8
Spearman Rank Order Correlation between landscape metrics computed on CORINE Land Cover Map and runoff-data

<table>
<thead>
<tr>
<th>BOD\textsubscript{7}</th>
<th>COD\textsubscript{K\textsubscript{MnO}_4}</th>
<th>Total-N</th>
<th>Total-P</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td><strong>-0.53</strong></td>
<td>-0.23</td>
<td>0.38</td>
</tr>
<tr>
<td>ED</td>
<td><strong>-0.47</strong></td>
<td>-0.10</td>
<td><strong>-0.56</strong></td>
</tr>
<tr>
<td>SHAPE_MN</td>
<td>0.23</td>
<td><strong>0.66</strong></td>
<td><strong>-0.44</strong></td>
</tr>
<tr>
<td>ENN_MN</td>
<td>0.12</td>
<td>-0.23</td>
<td><strong>0.62</strong></td>
</tr>
<tr>
<td>CONTAG</td>
<td><strong>-0.15</strong></td>
<td><strong>-0.59</strong></td>
<td>0.13</td>
</tr>
<tr>
<td>PRD</td>
<td>0.02</td>
<td>0.05</td>
<td>-0.20</td>
</tr>
<tr>
<td>SHDI</td>
<td>0.13</td>
<td>0.26</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Significant correlation coefficients are in bold; \( p < 0.05 \). See Table 2 for explanation of landscape metrics’ abbreviations.
Fig. 8. Relationship between patch density, BOD$_7$, and proportion of natural areas.

Fig. 9. Relationship between patch density, COD$_{K_{2}MnO_{4}}$, and proportion of natural areas.
Fig. 10. Relationship between edge density, total-N, and proportion of urban land use.

Fig. 11. Relationship between mean shape index, total-N, and proportion of urban land use.
Fig. 12. Relationship between mean shape index, total-N and proportion of natural areas.

Fig. 13. Relationship between mean euclidean nearest neighbor distance, total-N, and proportion of urban land use.
therefore, Fig. 9 indicates that the relationship between PD and COD_{KMnO_4} is not causal.

The edge density significantly correlated with organic matter and total-N runoff. In the case of total-N, the results might be influenced by point pollution sources (Tables 6 and 7). Fig. 10 demonstrates that, despite the influence of point pollution sources on ED and total-N, with increasing ED values, the total-N concentration is clearly decreasing. It refers to the ability of landscapes with more complex configurations to retain more nutrients.

The mean shape index significantly correlated with COD_{KMnO_4} and total-N runoff (Table 8), but depended considerably on land cover, and the interpretation of these results was therefore unusable.

Mean shape index significantly correlated with the proportion of urban land use. This relationship may be caused by the correlation between total-N and the mean shape index (Fig. 11). At the same time, the mean shape index correlated with total-N and the proportion of natural areas (Table 7 and Fig. 12).

Correlation analysis of the mean euclidean nearest neighbor distance showed that the total-N runoff is greater in the case of more isolated patches, but the index itself correlated significantly with the proportion of urban land use (Fig. 13).

The negative relationship between contagion and the COD_{KMnO_4} value indicated unexpectedly greater organic matter runoff from more disaggregated landscapes. The COD_{KMnO_4} runoff correlated significantly with agricultural land use, which points to low humic- and fulvic-acid-based organic matter runoff from agricultural areas (Fig. 14).

The patch richness density (PRD) and Shannon’s diversity index (SHDI) showed no expected correlations with water quality data (Table 8), although SHDI correlated significantly with the proportion of fens (Table 7). The diversity metrics’ (e.g., the SHDI) ability to predict nutrient and organic matter runoff from catchments was not good.

In literature, we could not find exact comparative material for the relationship between landscape metrics and water quality parameters chosen in this study. However, different studies confirm the basic outcomes of this study which show that there are lower nutrient and organic material losses from
landscapes with higher heterogeneity (Jones et al., 2001; Chen et al., 2002; Gergel et al., 2002). Landscape metrics are easily computed mathematical values that have some indicative value for water quality. Therefore, they open a new opportunity to use them as indicators for water quality in water management. For example, if we find that catchments’ edge density is very low and nutrients runoff is high, then we should favor changing the landscape more heterogeneous, e.g., fields and grasslands should intersperse, plant hedges as it is well known that riparian zones reduce nutrients runoff from catchments (Kuusemets and Mander, 2001; Baker et al., 2001, Jones et al., 2001; Gergel et al., 2002; McClain et al., 2003).

However, we pointed out complicated behavior of landscape metrics because of their varying responses to changes in scale and spatial pattern, there are several problems in landscape pattern analysis using landscape metrics. We agree with Li and Wu (2004) who suggested before any kind on landscape analysis carefully consider which metrics to use and to determine how to interpret them. In case of our study also caveats of correlation analysis with landscape metrics (Li and Wu, 2004) were carefully considered (discussed in previous sections) but they also need further study in order to be sure in causal relationships between landscape metrics and nutrient and organic matter runoff from catchments.

4. Conclusions

Changing grain size has a significant effect on landscape metrics. The responses of landscape metrics to changing grain size vary significantly among different landscape metrics and across different landscapes. This is mainly because of different factors that affect the behavior of landscape metrics. The rapid decrease in edge density values when changing grain size is caused by the simplification of edges. Also, it seems that landscapes of complex configuration show a greater decrease in their edge density values, reaching the same value as homogenous landscapes, i.e., at some point of spatial resolution the difference between landscapes disappears. The same effect appeared in the case of patch density. The reason for this behavior is the elimination of small complex parts of edges and small patches, which are often present in complex landscapes. Diversity metrics are sensitive to changing grain size when the number of classes starts to change.

Contagion and mean euclidean nearest neighbor distance are directly dependent on grain size; therefore, they should be used and interpreted carefully in case of changing grain size.

A significant difference was found between the relationships derived from the Base Map analysis and the CORINE Land Cover Map analysis. In the case of the Base Map, landscape metrics strongly correlated with land use and showed no expected relationships with water quality data. It points to the importance of land use classification in such kinds of analyses.

According to the CORINE Land Cover Map analysis, many indexes significantly correlated with water quality data. The strong relationship between the patch density and the COD\textsubscript{KMO}_4 value is most likely caused by the fact that both parameters were significantly correlated with the proportion of natural areas. However, the relationship between the values of edge density and the total-N and BOD\textsubscript{7} seemed to be causal, which is indicative of the ability of landscapes with more complex configurations to retain more nutrients and organic matter.

The mean shape index significantly correlated with water quality data but depended too strongly on land use. Therefore, no conclusions can be drawn from any of the results regarding the influence of landscape configuration on nutrients and organic matter concentration in river water.

The total-N concentrations are greater in more isolated patches (greater value of the Mean Nearest Euclidean Neighbor Distance). The total-N depends on both land use and landscape metrics; however, our data did not allow us to determine the detailed influence of either factor on total-N runoff.

A negative correlation between the contagion and the COD\textsubscript{KMO}_4 value indicated greater organic material losses from less compacted and more mosaic catchments. A reason for this relationship is probably the dependence of the index on the proportion of fens, bogs and mires, and agricultural land use, which made the results hard to interpret. Diversity metrics seem not to be good indicators for predicting nutrient and organic matter runoff from catchments.
Spatial resolution may have had a significant effect on our results, since changes in grain size have various impacts on different landscapes. For example, with increasing grain size, the edge density of more fragmented landscapes decreases more rapidly than in catchments with homogenous landscape structure, while the water quality data may remain the same.

Nutrient and organic matter runoff is influenced by land use and landscape metrics. As the landscape metrics depend on pixel size, topographic scale, and land use classification, and as the effect of land use on water quality in catchments is higher than that of other factors, it was impossible to separate the influence of land use pattern from the influence of FRAGSTATS-based landscape metrics.

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